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Cold Start on Online Advertising Platforms: Data-Driven Algorithms and Field Experiments

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Online Advertising Platform

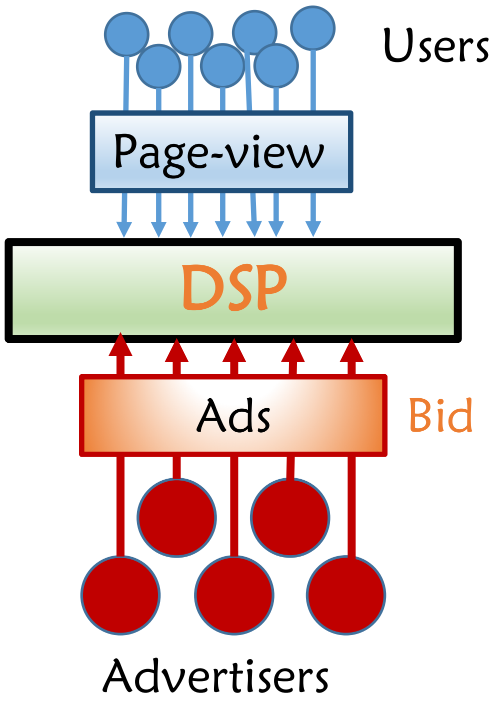
- Online advertising platform: Demand Side Platform (DSP)

- Fundamental question of a DSP:

> When an ad request (page view) arrives, which ad should be displayed to her?

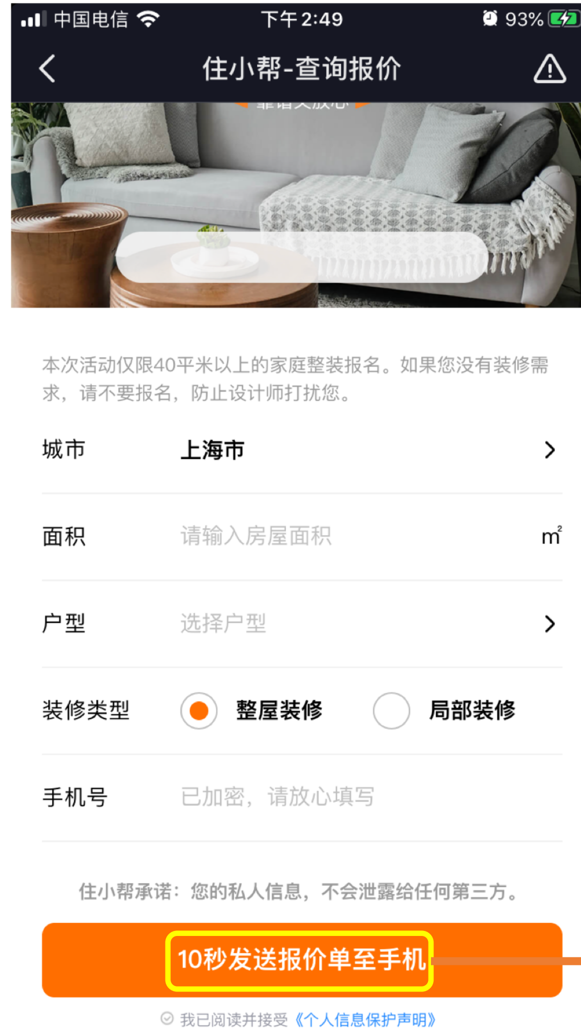
- Core business logic:

> The DSP runs large-scale auctions to determine which ad to display, in order to maximize the platform's revenue.



Performance-Based In-Feed Ads

Click-Through Rate (CTR)



Conversion Rate (CVR)

Ad Impression on the Platform

External Site of Advertiser

DSP and Advertisers

- Performance-based ads: More conversions/actions at a low cost (i.e., high Return on Investment)
  - Mobile games: Activation & deposit
  - eCommerce: Activation & purchase

- Auction Mechanism & Billing Option: Optimized Cost-Per-Click (oCPC)
  - The advertisers bid on conversions and pay upon clicks (a compromise between the advertisers and the DSP).
  - The ads are ranked by the expected cost-per-mile (eCPM), which is the expected revenue per unit impression.
  - The impression is allocated to the ad with the highest eCPM.
  - First-price auction.

Mechanism	Charged-upon	Fee-Deduction	Rank-by
oCPC	click	pCVR * bid_convert	eCPM = pCTR * pCVR * bid_convert

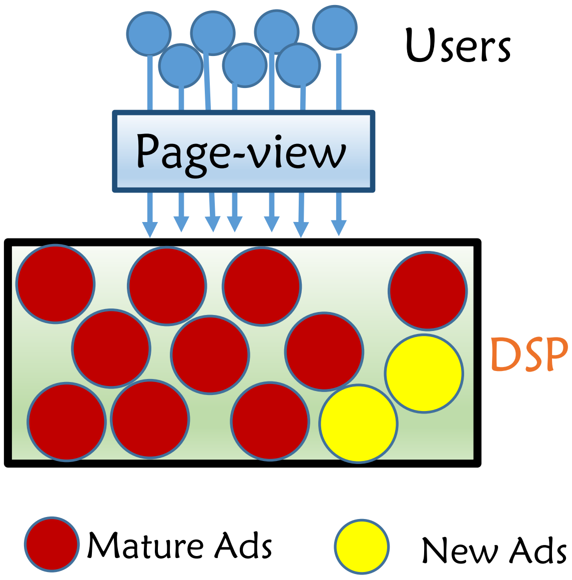
pCTR (predicted CTR) and pCVR (predicted CVR conditioned on click) are produced by underlying deep neural networks of the DSP

- The bids are more like target costs-per-action (CPA), instead of real costs.
  - The platform adjusts the bid for conversions in real-time through the Proportional-Integral-Derivative (PID) controller to control the realized CPA.

Cold Start on DSP

- New ads: No sufficient data to estimate pCTR and pCVR accurately.
  - Unclear revenue implications for the DSP.
  - Successful cold start of new ads thickens the ad pool and boosts advertiser retention.

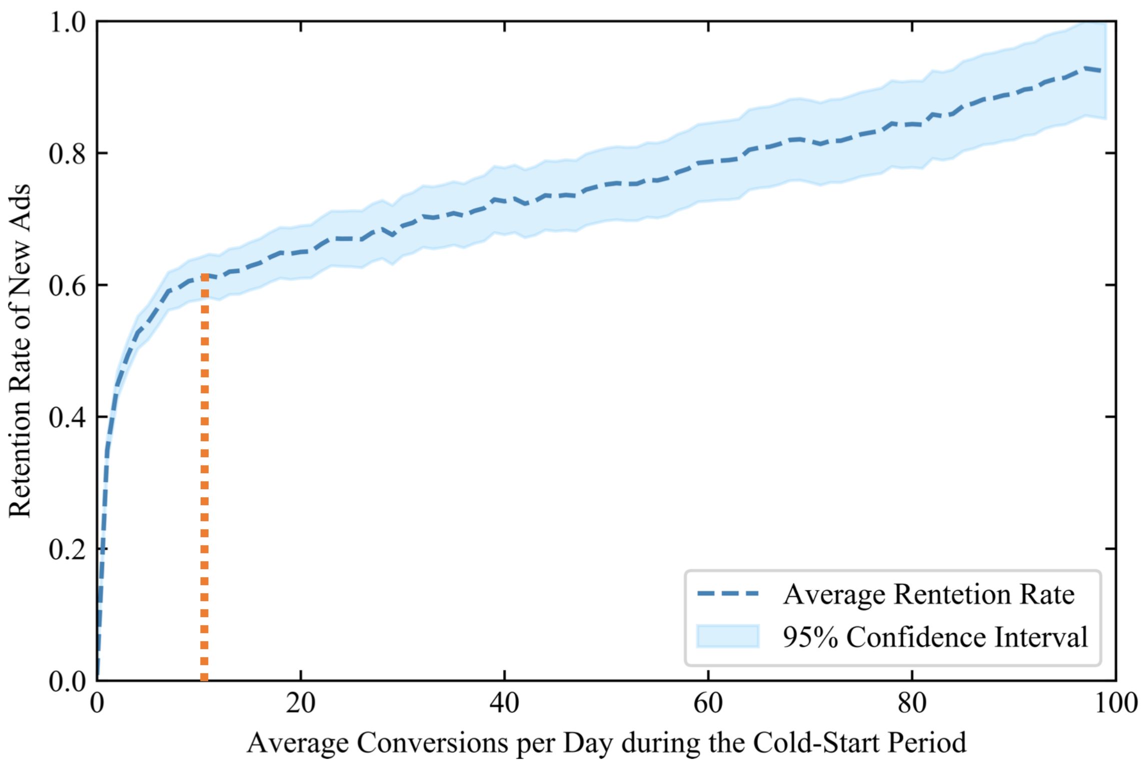
- Mature ads: High and stable revenues, minimally affecting user experiences.



Core Problem: How to allocate user impressions between new and mature ads to balance the short-term revenue and the long-term cold start value?

Exploitation **vs** Exploration

Cold Start on DSP: Ad Retention



- X-axis: # of conversions in the first 3 days.
- Y-axis: Proportion of ads that will stay active on the DSP every single day in the next 2 weeks.
- Every thing is rescaled.

- Key observation: If the # of conversions in the cold start period surpasses 10, the long-term retention and value soon flatten.

- The # of new ads with # of conversions ≥ 10 is a key metric to evaluate ad cold start effectiveness.

- The phenomenon of the left figure is robust with respect to different definitions of ad retention.

Key Research (and Business) Questions

- With inaccurate predictions of CTR and CVR for new ads, how to smartly balance short-term revenue and long-term market thickness (i.e., cold start value)?

Primal-dual based MAB algorithms:
Shadow Bidding with Learning (SBL)

- With different ads competing for the same page-views, how to unbiasedly estimate the value of our proposed algorithm?

User-ad two-sided experiment framework

Related Literature

- Ad Cold Start: **More accurate** CTR and CVR predictions for new ads.
  - Dave and Varma (2012, 2014), Zhou et al. (2018), Choi et al. (2020), etc.

- Contextual Bandits: Establishing sublinear regret bounds with **optimization oracle**.
  - Langford and Zhang (2007), Chu et al. (2011), Bandanidiyuru et al. (2013), Agrawal et al. (2014), Agrawal et a. (2016), Jacot et al. (2018), Arora et al. (2019), etc.

- Operations problem with online learning: Bandit learning algorithms applied to **revenue management and inventory** problems.
  - Besbes and Zeevi (2009), Nambiar et al. (2019), Chen et al. (2019), Golrezaei et al. (2019), etc.

- Experimental evaluations of algorithms on two-sided platforms: Debiasing the estimate when **SUTVA does not hold**.
  - Ha-Thuc et al. (2020), Johari et al. (2020), etc.

Highlight of Main Contributions

- Modeling:
  - Formulation of ad cold start as a data-driven optimization model under uncertainty
- Algorithm:
  - SBL algorithm: Duality + MAB + neural networks
  - Bridging the gap between learning theory and online advertising practice
- Experiment:
  - Two-sided experiment to evaluate a bandit algorithm
  - Novel experiment design to restore SUTVA
  - Unbiasedly demonstrate the significant value of the SBL algorithm in ad cold start

Model for Cold Start

- Problem setting: First-price auction, CVR=pCVR=1 (oCPC = CPC)
- A set of new ads $A := \{1, 2, \ldots, K\}$, with bids $\{b_1, b_2, \ldots, b_K\}$
- A set of user impressions, arriving at the DSP sequentially: $[T] := \{1, 2, \ldots, T\}$
- Context associated with each user: $x_t \in X$, *i.i.d.* on a countable set X, $x_t \sim \mathcal{D}$
- $v_{ij} = 0, 1$: Whether a user with context_i clicks ad_j; $y_{tj} = 0, 1$: Whether display ad_j to user_t
- CTR: $c_{ij} := E[v_{ij}]$, $\hat{c}^t_{ij}$:=pCTR estimate by the underlying DNN in round t
- Sequence of events in each round t:

Platform observes the context x_t → Platform estimates pCTR $\hat{c}^t_{x_t,j}$ for all ad_j → Platform decides which ad to display y_{tj} → Click-through outcome $v_{x_t,j}$ realized

Reward Upper Bound and Regret

- Our objective is to identify a policy π to maximize the expected reward $E[\Gamma]$:

$$\Gamma := \underbrace{\sum_{j=1}^{K} b_j \left(\sum_{t=1}^{T} v_{x_t,j} y_{tj}\right)}_{\text{Short-term revenue}} + \underbrace{\sum_{j=1}^{K} \beta_j \min\left\{\sum_{t=1}^{T} v_{x_t,j} y_{tj}, \alpha T\right\}}_{\text{Long-term cold start value}}$$

- β_j is the cold start value of ad_j, determined by business sense and simulation.
- αT is the threshold for cold start success.

Lemma (Fluid upper bound). We have the following upper bound for the expected reward:

$$\frac{1}{T} E_{\mathcal{D},\pi}[\Gamma] \leq \text{OPT} := \max_{y_i \in \Delta_A} \left\{ \sum_{j=1}^{K} E_{i\sim\mathcal{D}}[c_{ij} y_{ij} b_j] + \sum_{j=1}^{K} \beta_j \min\left\{ E_{i\sim\mathcal{D}}[c_{ij} y_{ij}], \alpha \right\} \right\}$$

where Δ_A is the distribution over all the ads and $y_i = (y_{i1}, y_{i2}, \ldots, y_{iK}) \in \Delta_A$ is the ad assignment distribution for a user with context i.

- The regret of a policy: $\text{Reg}(\pi) := T \cdot \text{OPT} - E_{\mathcal{D},\pi}[\Gamma]$
- We seek to design an algorithm with sublinear regret and implementable on a real DSP.

Empirical Reward and Ad Allocation

- Empirically optimal ad allocation policy at round t:

$$\max_{y_{sj}\geq 0,\ \sum_{j\in A} y_{sj}\leq 1} \underbrace{\sum_{s\leq t-1}\sum_{j\in A} \overbrace{\hat{c}^s_{ij}}^{\text{eCPM of ad\_j in round s}} b_j y_{sj}}_{\text{Short-term revenue}} + \underbrace{\sum_{j\in A} \beta_j \min\left\{ \sum_{s\leq t-1} \hat{c}^s_{ij} y_{sj}, \alpha(t-1) \right\}}_{\text{Long-term cold start value}}$$

- Linearize:

$$\max_{y_{sj}\geq 0,\ u_j\geq 0} \quad \sum_{s\leq t-1}\sum_{j\in A} \hat{c}^s_{ij} b_j y_{sj} + \sum_{j\in A} \beta_j [\alpha(t-1) - u_j]$$

$$\text{s.t.} \quad \sum_{j\in A} y_{sj} \leq 1,\ \forall s\leq t-1, \quad \sum_{s\leq t-1} \hat{c}^s_{ij} y_{sj} + u_j \geq \alpha(t-1),\ \forall j\in A$$

  - u_j is the number of conversions below the threshold.
  - The model has a too high dimension to solve efficiently online.

Duality and Shadow Bidding

$$\min_{\lambda_j \in [0,\beta_j]} \sum_{s \le t-1} \max_{j \in A} \{\underbrace{\hat{c}^s_{ij}(b_j + \lambda_j)}_{\text{Adjusted eCPM for ad\_j}}\} - \alpha(t-1) \sum_{j \in A} \lambda_j$$

- Only K decision variables: Can be efficiently solved using sub-gradient descent!
- λ_j is the dual variable for the cold start reward constraint: $\sum_{s \le t-1} \hat{c}^s_{ij} y_{sj} + u_j \ge \alpha(t-1)$
  - We call λ_j the shadow bid of ad_j.
- The shadow bid λ_j is bounded by the cold start value of ad_j, β_j
- Actionable Insight:
  - Smartly computing the shadow bid of each new ad and incorporating it into the auctions of the DSP could effectively trade off short-term revenues with long-term cold start values!
  - Naturally fit into the ad auction system of a DSP in practice.

Shadow Bidding with Learning (SBL)

Shadow Bidding with Learning (SBL) Algorithm

- Update shadow bids at rounds $\tau_1, \tau_2, \dots$, where $\tau_{m+1} - \tau_m = \tau_m - \tau_{m-1} = O(T^{\frac{2}{3}})$

- For each round t=1, 2, 3, ⋯, T
  1. Observe the context $x_t = i$. With probability $\epsilon_t = t^{-\frac{1}{3}}(K \log t)^{\frac{1}{3}}$, explore uniformly at random; with probability $1 - \epsilon_t$, display the ad $\mathrm{argmax}_j \hat{c}_{ij}^t (b_j + \lambda_j)$, with an arbitrary tie-breaking rule.

  2. If $t = \tau_m$, solve the empirical dual program to update λ, and update $m \leftarrow m + 1$

  3. Observe the click-through outcome, and update $\hat{c}_{ij}^{t+1}$

Existing approaches in the literature:

- Based on empirical risk minimization oracle.
- Regret benchmarked with the best policy in a policy set, dependent on the policy set size.
- Of theoretical nature, not scalable and implementable on a real DSP.

vs

SBL Algorithm:

- Dual + MAB (epsilon greedy) + ML Oracle.
- Optimal primal ad allocation with the dual solution, which can be obtained efficiently.
- Leveraging the underlying ML Oracle.
- Implementable on a large-scale DSP in practice with minimal changes to the system.

Theoretical Performance Guarantee of SBL

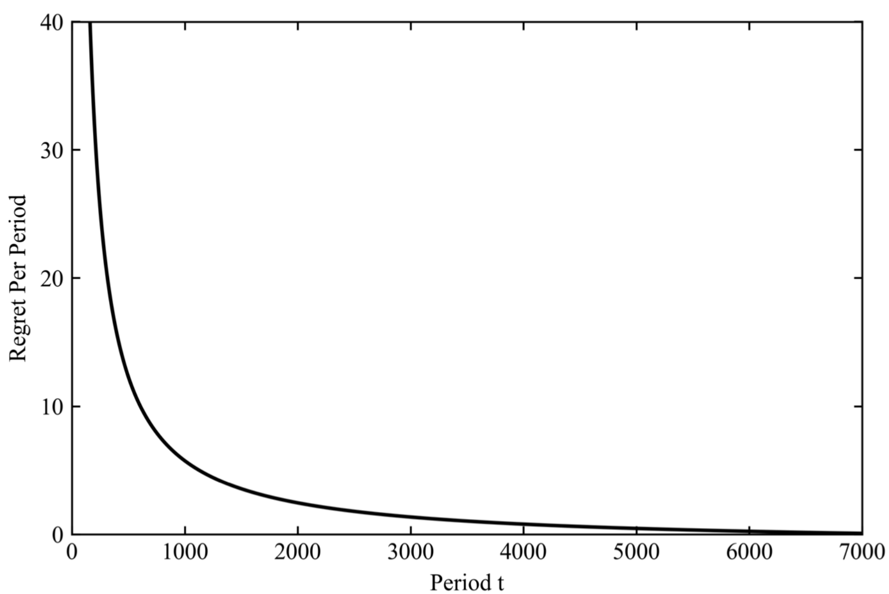
- Machine learning oracle assumption: With probability at least $1-\delta$, the estimate $\hat{c}_{ij}^t$ satisfies

$$|\hat{c}_{ij}^t - c_{ij}| \le O\left(\sqrt{\log(1/\delta)d/n_j^t}\right)$$

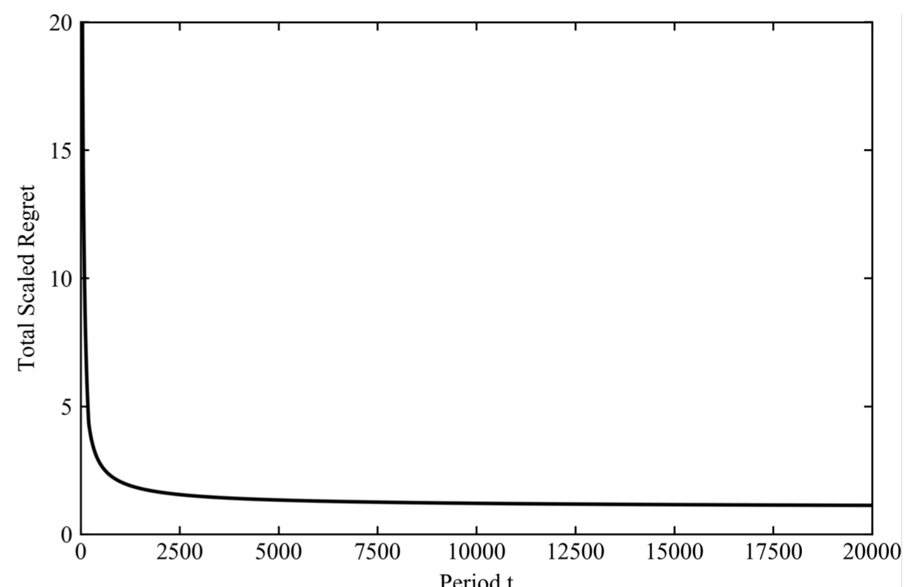
where d is the dimension of the underlying machine learning oracle to obtain the pCTR $\hat{c}_{ij}^t$, n_j^t is the number of impressions for ad_j by round t.

- Satisfied by (i) linear regressions; (ii) regression trees; and (iii) fully connected neural networks.

Theorem (Regret bound). The expected regret of SBL is bounded by $O(T^{\frac{2}{3}}K^{\frac{1}{3}}(\log T)^{\frac{1}{3}}d^{\frac{1}{2}})$.



Average Regret per Period



Total Regret Scaled by $t^{-\frac{2}{3}}(\log t)^{-\frac{1}{3}}$

Sketched Regret Analysis

- Key challenges:
  - History-dependent cold start reward (i.e., the knapsack bandit setting)
  - Dual-based bidding strategy implemented on the primal space
  - Regret dependent on the underlying machine learning oracle to predict CTR
  - Too high variance with Inverse Propensity Score to estimate the expected reward

- Key ideas and the road map to overcome the challenges:

- Establish approximate complementary slackness and bound the duality gap between the empirical primal and the empirical dual, due to tie breaking in SBL by $O(T^{\frac{1}{3}}(\log T)^{\frac{1}{3}}K^{\frac{1}{3}})$
- Build an auxiliary reward process independent of history: Each click of ad j generates a reward of $b_j + \beta_j$, irrespective of whether the threshold αT is met. Under SBL, bound the gap between the auxiliary reward process and the optimal reward by $O(T^{\frac{2}{3}}(\log T)^{\frac{1}{3}}K^{\frac{1}{3}}d^{\frac{1}{2}})$
- Under SBL, bound the gap between the auxiliary reward process and the true reward process by $O(T^{\frac{1}{2}}(\log T)^{\frac{1}{2}}K^{\frac{1}{2}})$
- Putting the above bounds together yields the expected regret of SBL is $O(T^{\frac{2}{3}}(\log T)^{\frac{1}{3}}K^{\frac{1}{3}}d^{\frac{1}{2}})$

Online Implementation of SBL (oSBL)

Online Shadow Bidding with Learning (oSBL) Algorithm

- Update shadow bids at rounds $\tau_1, \tau_2, \cdots$, where $\tau_{m+1} - \tau_m =$ 1 hour, set $\alpha T = 10$, $\beta_j = 2b_j$

- For each round t=1, 2, 3, ⋯, T
  1. Observe the context $x_t = i$. Choose top 150 (new & mature) ads and another 15 randomly picked new ads to join the auction.

  2. Obtain $\hat{c}^t_{ij}$=pCTR*pCVR. Display $\mathrm{argmax}_{j\in[K_t]}\hat{c}^t_{ij}(b_{tj}+\lambda_j)$, where b_{tj} is the system bidding price calculated by the real-time PID system and $[K_t]$ is the set of the 165 ads who join the auction.

  3. If $t = \tau_m$, sample 4% of the auctions in the past hour $\mathcal{H}_t$ and update the shadow bids λ by

$$\min_{\lambda_j\in[0,\beta_j],\forall j\in[K],\lambda_j=0,\forall j\in[K']} \sum_{s\in[\mathcal{H}_t]} \max_{j\in[K_s]}\{\hat{c}^s_{ij}(b_{sj}+\lambda_j)\} - \alpha|\mathcal{H}_t| \sum_{j\in[K_s]}\lambda_j$$

     where [K] is the set of new ads and [K'] is the set of mature ads

  4. Observe the click-through outcome, and update $\hat{c}^{t+1}_{ij}$

- Conversions are incorporated into the algorithm (CVR and pCVR are much smaller than 1).
- For a mature ad, the shadow bid is 0.
- Shadow bids are updated every hour based on sampled data, implemented on top of the PID system.
- More like uniform exploration than epsilon-greedy.
- Cold start value is set at twice as much as the target CPA of the ad: $\beta_j = 2b_j$

Implementing and Testing SBL

- SBL algorithm implemented on a large-scale video-sharing platform (Platform O)
- How to unbiasedly evaluate the SBL algorithm?
- Naive one-sided experiment designs:
  - Ad-side randomization:

	Treatment New Ads	Control New Ads	Non-Experiment New Ads	Mature Ads
100% UV	Treatment Condition	Control Condition		

  - User-side randomization:

	100% New Ads	Mature Ads
Treatment UV	Treatment Condition	
Control UV	Control Condition	
Non-Experiment UV		

Treatment = oSBL algorithm; Control = baseline algorithm (uniformly increase the bidding price of all new ads)

Violation of SUTVA

- Ad-side randomization:

	Treatment New Ads	Control New Ads	Non-Experiment New Ads	Mature Ads
100% UV	Treatment Condition	Control Condition		

- User-side randomization:

	100% New Ads	Mature Ads
Treatment UV	Treatment Condition	
Control UV	Control Condition	
Non-Experiment UV		

- SUTVA (Stable unit treatment valuation assumption): The assignment of one unit to treatment or control will not affect the outcome of another unit.

- Ad-side randomization: 120% overestimate
  - Violation of SUTVA: New ads from different groups compete on the same user impressions.

- User-side randomization: 40% underestimate
  - Violation of SUTVA: The effect of oSBL spills over to the control group users.

Two-Sided Experiment Design

- A novel two-sided experiment design:

	20% Treatment New Ads	20% Control New Ads	60% Non-Experiment New Ads	Mature Ads
33% Treatment UV	B11	B12	B13	B14
33% Control UV	B21	B22	B23	B24
33% Non-Experiment UV	B31	B32	B33	B34

- Blue = oSBL, white = baseline algorithm, grey = ad blocked (to remove externalities)
- SUTVA restored! Able to generate unbiased estimates.
- Impact on long-term cold start value: Comparing B11 with B22
- Impact on short-term revenue: Comparing B11+B13+B14 with B22+B23+B24
- Experiments conducted between May 23, 2020 and May 30, 2020

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Randomization Check

Table 2 Randomization Check of the Experiment

Panel A: Randomization Check on the Ad side		Treatment ads	Control ads	p-value of t-test
	Number of New Ads	34,605	34,076	
Statistics during the Experiment	Bidding Price	48.14 (52.24)	48.17 (51.45)	0.91
	Proportion of Ads for iOS Users	24.1% (0.427)	24.2% (0.428)	0.98
	Proportion of Ads for UI Version X	30.3% (0.459)	28.3% (0.450)	0.69
	Proportion of Ads in Game Industry	13.8% (0.086)	13.7% (0.081)	0.98
	Proportion of Ads in Education Industry	0.75% (0.086)	0.67% (0.082)	0.93
	Proportion of Ads in Finance Industry	1.75% (0.131)	1.87% (0.135)	0.93
Panel B: Randomization Check on the UV side		**Treatment UV**	**Control UV**	**p-value of t-test**
	Number of Users	197,460,792	197,401,621	
Statistics during the Experiment	Male Proportion	0.540 (0.491)	0.540 (0.491)	>0.99
	Average Revenue per User	0.95 (27.15)	0.95 (27.14)	>0.99
	Average Impressions per User	23.36 (17900)	23.24 (17864)	0.95
	Average Clicks per User	3.195 (4455)	3.20 (4458)	0.99
	Average Conversions per User	0.041 (32.80)	0.040 (32.25)	0.88

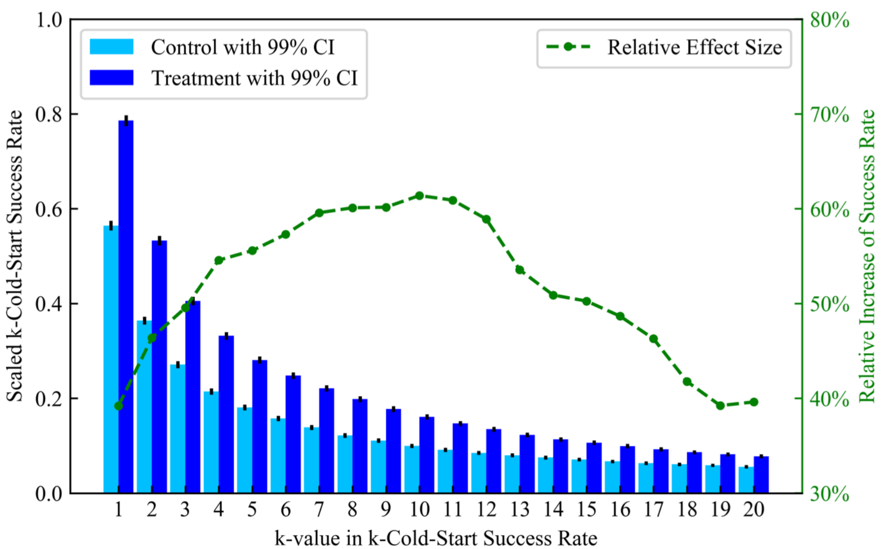
Note: Standard deviations in Panel A are clustered at the ad level and reported in the parentheses. Standard deviations in Panel B are clustered at the user level and reported in the parentheses. To protect sensitive data, the reported metrics are rescaled.

Experiment Results

- oSBL algorithm has caused:

Metric of Interest	Cold start success rate	Cold start reward	Total objective value	Total short-term revenue	CTR Prediction AUC
Relative Change	+61.62%***	+47.71%***	+0.147%***	-0.717%**	+7.48%*

- Given the gigantic scale of Platform O, the experiment implies a sizable hundred-million-dollar boost in ad revenue per year.
- Two-sided network effects would give rise to a much stronger increase in the total long-term value of oSBL.
- Results are robust if we run regression models and control user- and ad- specific features.



Robustness of Results

Takeaways

- SBL Algorithm: A smart algorithm to bridge the gap between bandit learning theory and the ad cold start practice.

- Two-sided experiment: Unbiasedly estimate the value of SBL for a large-scale online advertising platform.

- SBL and two-sided experiment have the potential to optimize and evaluate more general recommender systems of online two-sided platforms.

Thank You!

Questions?